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COMPARATIVE EVALUATIONS OF THE RADC/HSU TEXTURE MEASUREMENT SYSTEM WITH PERCEPTUAL ANALYSES

LEVEL III

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Final Report

By

SHIN-YI HSU

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SUSQUEHANNA RESOURCES AND ENVIRONMENT, INC.

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Aspects of the enormously important pattern recognition problem were examined. Real-world, digitized-image information from high and low resolution aerial photographs of different and similar terrain-types was used. We compared human judgments of overall visual differences among chloropleth representations with computer solutions based on the RADC/Hsu system. The work has resulted in new methodological and theoretical perspectives (including Masters' scaling technique) which provide means for better defining and understanding both human and computer information handling systems when highly complex, remotely-sensed, real-world data are involved.

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COMPARATIVE EVALUATION OF THE RADC/HSU TEXTURE MEASURE/CLASSIFIER SYSTEM WITH HUMAN PERCEPTUAL ANALYSIS

Final Report

A. GENERAL INTRODUCTION

The perception of "texture" is considered an important characteristic for pattern identification/recognition/classification problems presented to man or machine. Many attempts and approaches to understanding visual texture perception by humans have been undertaken--some notable references include: Koffka, 1935; Gibson, 1950; Avery, 1968, Lipkin and Rosenfeld, 1970; Pickett, 1970; Kolers, 1972; Ginsburg, 1973; Reed, 1973; Campbell, 1974; Pollen and Taylor, 1974; Pribram, 1974; Rosenfeld, 1975; Richards, 1978. In another context, technological advances in the collection of remotely sensed image information and computer science have resulted in much research centered on the development of "texture feature" measures based on digitized imagery for automated solutions to the poorly understood pattern recognition problem (see, e.g., Haralick, 1979 for a recent review). However, only a few studies thus far have attempted to directly relate such digitized image measurements to the visual texture recognition process: e.g., Haralick's (1973, 1975) greytone co-occurrence; Mitchell, Myers, and Boyne's (1977) Max-min Descriptor; Tamura, Mori and Yamawaki's (1978) texture feature extraction; and the RADC/Hsu (1977, 1978) texture measurement/classification system. We believe such attempts are of considerable importance since they provide the potential for new insights regarding both human and machine information processing as related to better understanding pattern recognition processes in both systems and for identifying approaches to establishing optimally synergistic

relations between machines and their creators. The need to develop such an effective rapprochement(s) is increasingly apparent as the avalanche of potentially useful information from advancing technological breakthroughs continues unabated, with virtually no end in sight. The ability to realize optimal utilization of such potential information has broad and strikingly dramatic implications for establishing advances in our knowledge in such diverse fields as microbiology and medicine, through ecology to cosmology and thus, of course, for national defense.

We recently reported (Hsu and Burright, 1980) some of our initial work concerned with identifying relationships between machine solutions and visual judgments of textural patterns based on real-world images. That paper, and our first Annual Report (S.R. & E., 1979) provide considerable detailed background relevant to our continuing efforts, so generously sponsored in the past two years by AFOSR, to attack this clearly awesome problem. This Final Report, then, will emphasize the findings, directions, and issues which our work has produced during the last year of grant support by AFOSR to Susquehanna Resources and Environment, Inc., with Dr. Hsu as principal investigator. While no single approach alone can hope to provide all the answers to the enormous problem area outlined above, we strongly believe that the analytic approaches we have been able to develop as a result of this AFOSR sponsored program do provide some important avenues for new perspectives on this most important research area--a general area of research which we, as a nation, simply cannot afford to ignore.

As detailed in our 1978-79 Annual Report (S.R. & E.) two intriguing points have provided the basic impetus (and hypotheses) underlying our current work: 1) A variety of evidence from the psychological, psychophysical, physiological

and neurological literature strongly suggests that the visual perceptual system may well employ about three "filters/channels/dimensions" in analyzing visual patterns;2) the RADC/Hsu machine system can successfully employ three feature variables defined by average grey-level, first neighbor and second neighbor contrasts to classify digitized image information.

B. SUMMARY OF THE BASIC APPROACH

Our basic approach to the problems outlined above have involved comparing human similarity/difference judgments of textural patterns based on real-world images with outcomes of the RADC/Hsu machine analysis which employs local statistics from small (3 x 3) moving pixel windows (see Annual Report 1978-79, appended). Such comparisons include the use of individual difference multi-dimensional scaling technique which allows the construction of stimulus dimension models for human and machine processes using microtexturally common (and specifiable) image conditions. In general, our results indicate that such analytic approaches can help provide: 1) clearer criteria for defining "perceptually-based" automated analysis of remotely-sensed data; and 2) better specification of conditions which produce inter-and/or intra-individual differences in the weighting of stimulus dimensions when judging differences among visual patterns. In this context, our data also seem to corroborate the idea that a "micro-textural approach" to these problems is appropriate, since it can specify the building blocks which define complex configurations of stimulus arrays "perceived" either by man or machine.

C. PERCEPTUAL SCALING MODELS AND METHODS

In our first year effort on this project (S.R. & E., 1979) we established that human subjects, not surprisingly, often use dimensions which might well be labelled "tone" and "texture"--but additional dimensional spaces and/or variations within dimensions may certainly be employed by the human observer when judging differences

among complex visual patterns. During the first year we conducted texture perception experiments on two data sets: 1) four differentially but systematically scaled population density maps (20 subjects); and 2) four choropleth representations of terrain types based on relatively low altitude, achromatic, aerial photographs (40 subjects). Using a non-metric individual difference multi-dimensional scaling method proposed by Takane, Young and deLeeuw (1977), we explored a variety of "perceptual models." For instance, we fixed a "texture-tone," two-dimensional perception model based on parameters specified by the RADC/Hsu feature extractor/classifier solution. When the subjects solution spaces were fitted into this pre-determined texture-tone perception model, it was determined that about 50 percent of the subjects displayed a very good fit, 10 percent a good fit, 15 percent a moderate fit and the remaining 25 percent showed either a poor,or no fit at all. It should be noted that, in our case (four stimuli per set), the maximum number of dimensions available using the Takane, et al, method is two (n-2).

The fact that 25 percent of the subjects had different perceptual spaces than that specified by the fixed model indicates that the proposed two dimensional texture-tone model cannot adequately explain both the possible dominant scales and specific individual scales existing in the human data set. To detect the existence of additional dominant perceptual dimensions, we tried to consider other dimensions in place of one of the texture-tone dimensions and matched the solutions against that of the original texture-tone model. This effort proved to be less than satisfactory because the above analysis could not yield distinctive patterns. This lead us to conclude that there is a definite need to develop a new multi-dimensional scaling method that is capable of revealing (at least in descriptive terms) all possible dominant and individual-specific

spaces defined by the individual perceptual judgments obtained. Indeed, one of our major efforts during the second year of this project was devoted to establishing such new methodology. Thus, this section of our report is devoted primarily to defining a new model which was developed by our research scientist, Dr. Timothy Masters, specifically to address these problems with scaling techniques. This new method is termed the Masters' supersaturated, individual differences, multi-dimensional scaling technique. Of course, at an individual subject level, the number of dimensions is still restricted by the number of stimuli involved (i.e., n-1).

I. DEFICIENCY OF THE EXISTING MODELS

From the above discussion and a literature review, it is clear that the existing multi-dimensional scaling models are very limited in revealing dimensions of human perceptual space because nearly all traditional methods involve locating the stimuli in a saturated space of maximum dimension n-1 (and usually less) and projecting these stimuli onto orthogonal axes. These axes define the scales and they are named by studying the projections of the stimuli on them. Major drawbacks of this approach can be noted as follows:

a. Especially if the number of stimuli is not large, interpretation of research results will be hampered by the limitation of the number of scales (n-1 or fewer).

b. Imposition of orthogonality on the scales is unnecessary and in most cases may well contradict reality.

c. The judgments of individual subjects for any given situation need not share a highly limited and common perceptual space. Certainly, the ability of perceptual/cognitive systems to create

dimensionality in "seeking" relatively simple order (cf. Kolers, 1972) would suggest why intra- and/or inter individual differences are truly a hallmark of data in the behavioral sciences in general. This limitation of methodology is alleviated somewhat by individual difference methods such as that of Takane, Young and deLeeuw employed in our 1978-79 Annual Report (S.R. & E.). However, such techniques still restrict the number of scales to a common set of n-1 (saturated) for ratio data and n-2 for interval and ordinal data.

d. Most scaling algorithms require prior specification of the dimensionality. Addition of another dimension will change the scales already found. Since in most research, the number of dimensions is unknown or to be determined after the analysis, this requirement is thus very undesirable.

II. PRINCIPLES FOR THE NEW SCALING MODEL

It is clear that a new scaling method should have the capability of solving the problems discussed above. Thus, the following principles guided the development of the Masters', supersaturated, individual differences, multidimensional scaling technique for extracting potential dimensions which appear (at least at a descriptive level) in data sets such as those generated by our perceptual judgments.

a. The number of scales can be greater than the number of stimuli.

b. Using a step-wise method, initially compute a dominant scale by which the subjects perceived the stimuli.

c. For each subject, find a perturbation of that dominant scale while maintaining the fundamental identity such that a measure of fit to the subject is maximized.

d. For each subject, decide (on the basis of the above measure of fit) whether that perturbed scale is actually being used by the subject.

e. If any subjects still have one or more perceptual scales remaining, define another, "deflated" common dominant scale and then go to Step b using the "deflated" configuration.

f. Instead of finding a dominant scale based solely on the data set, one may specify a scale or scales (e.g., based on parameters specified by aspects of the stimuli per se); the technique would then proceed by following Steps c through e using this "fixed model" approach.

g. The scales are oblique, instead of being forced into an orthogonal configuration.

III. DESCRIPTION OF THE COMPUTERIZED DATA ANALYSIS PROCEDURES-FIXED MODEL

Having developed this new scaling technique, we examined its strengths (and weaknesses) by employing it with the Terrain-Type data set (40 subjects) obtained during our first year effort and comparing the results with those obtained using the Takane, et al (1977) methods (S.R.& E.,1979). The new technique will be described in detail as we employed it with this data set and a fixed (user-specified) model:

a. Input data format: Dissimilarity matrices for all 40 subjects plus the RADC/Hsu classifier solution as subject 41. For instance:

Subject 1	Vegetation	Pavement	Edgepave
Pavement	5.00		
Edgepave	3.00	5.00	
Cultivated Field	3.00	8.00	3.00

etc.

b. Extract the first, user-specified scale and determine the sub-space over-lap between this specified scale and an individually perceived scale. This is similar to a goodness-of-fit analysis. Furthermore, the degree (called full weight) to which this scale is utilized by each subject for establishing judged differences among stimuli is computed. In our computerized procedures, these analyses are output in the following format.

1. The fixed scale after 0 deflation is

   (VEG-----CFLD------EGPV----------PAVE)

In fact, this is a "Brightness" scale based on overall mean brightness as specified by the RADC/Hsu system (S.R.& E., 1979). From Table 1 (page 9), it can be concluded that almost all of the subjects used the brightness scale to some extent; however, the average amount of use of the scale is only 0.47. That is, the remaining 53 percent of discrimination criteria in this data set has to be "explained" by scales other than this fixed "brightness" scale.

c. Extraction of a second, user-specified scale.

1. Data input: Configuration after 1 deflation.

   This step is similar to the concept of "residuals" in regression analysis. The data are still in a matrix format, such as:

Subject 1	Scale 1	Scale 2	Scale 3
VEG	0.21886	0	0
PAVE	0.92886	0	0
EGPV	-0.42362	0	0
CFLD	-0.72412	0	0

⋮

TABLE 1: The First Fixed Scale: Subjects' Subspace Overlap and Utilization Weight Analysis

Subject	Full Weight	Subspace Overlap
1	0.46	0.97
2	0.64	1.00
3	0.37	1.00
4	0.02	1.00
5	0.36	1.00
6	0.49	0.97
7	0.46	1.00
8	0.88	1.00
9	0.54	0.86
10	0.33	1.00
11	0.21	1.00
12	1.00	1.00
13	0.86	1.00
14	0.11	1.00
15	0.86	1.00
16	0.69	1.00
17	0.01	1.00
18	0.14	1.00
19	0.32	0.98
20	0.45	1.00
21	0.77	1.00
22	0.23	0.92
23	0.15	0.99
24	0.12	1.00
25	0.68	1.00
26	0.64	1.00
27	0.80	1.00
28	0.57	1.00
29	0.43	1.00
30	0.66	1.00
31	0.27	1.00
32	0.55	1.00
33	0.19	1.00
34	0.88	1.00
35	0.12	1.00
36	0.15	1.00
37	0.56	1.00
38	0.48	1.00
39	0.68	1.00
40	0.60	1.00
41*	0.99	1.00
Mean Weight (Excluding computer)	0.47	

*Subject 41 is a computer classifier solution.

Subject 3	Scale 1	Scale 2	Scale 3
VEG	0.31255	-0.24239	0
PAVE	-0.38832	-0.17255	0
EGPV	-0.82154	0.21152	0
CFLD	0.89732	0.20342	0

etc.

This shows that for each subject, the maximum number of scales with 4 stimuli is 3. The above examples also indicate that Subject 1 potentially has 1 scale left to be described, whereas Subject 3 has 2 scales left.

2. The second fixed scale is:

   (CFLD----VEGN----PAVE----------EGPV)

   indicating a "texture" dimension as defined by RADC/Hsu parameters (S.R.& E., 1979).

3. Following the same procedures described previously, we have "subspace overlap" and "full weight" for each subject regarding the relationship between this fixed scale and the subjects perceived dimension (see Table 2, page 11).

   Note that we are able to assign a cut-off regarding the subspace overlap; e.g., those ratios less than 0.95 will be regarded as "insignificant." The full weights of these subjects will then be nullified. Thus, in Table 2 (page 11), the average weight of 40 subjects using this texture dimension is 0.12.

TABLE 2: The Second Fixed Scale (an example)

Subject	Full Weight	Subspace Overlap
1	0.54	0.15
2	0.36	0.24
3	0.35	1.00
4	0.52	0.84
5	0.37	0.76
6	0.51	0.74
7	0.35	1.00
8	0.07	0.98
9	0.39	1.00
10	0.25	1.00
11	0.50	0.96
12	0	0
13	0.14	0.38
14	0.25	1.00
15	0.14	0.71
16	0.30	0.58
17	0.49	1.00
18	0.47	1.00
19	0.68	0.62
20	0.55	0.76
21	0.23	0.89
22	0.85	0.86
23	0.85	0.70
24	0.36	0.94
25	0.31	0.85
26	0.36	0.87
27	0.20	0.80
28	0.43	0.84
29	0.56	0.99
30	0.21	0.96
31	0.18	0.88
32	0.44	0.83
33	0.55	0.98
34	0.11	0.15
35	0.10	1.00
36	0.29	0.95
37	0.44	0.76
38	0.51	0.44
39	0.31	0.84
40	0.40	0.37
41*	0.01	1.00
Average	0.35 with only those (14/40) subjects having a subspace overlap ratio of 0.95 or larger; whereas the overall average with 40 subjects is 0.12.	

*Subject 41 is a computer classifier solution.

Up to this step of analysis, the new scaling method is more or less similar to the method proposed by Takane, Young and deLeeuw which we employed during the first year of this sponsored research (S,R,& E.,1979). The sum of the average utilization ratios (full weights) from Scale 1 (brightness) and Scale 2 (texture) is 59 percent (0.47 + 0.12). This means that 41 percent of the total ("supersaturated") utilization weight remains to be explained by other dimensions. Relative to the old procedure (Takane, et al), this 41 percent of "unexplained" variance was translated into 25 percent of subjects being classified as having either poor-fit or no-fit to the fixed "tone-texture" space.

d. Extraction of the third user-specified scale.

Using our new method we are able to extract more scales to account for this large amount of unexplained variance using either additional fixed scales or computer extracted scales.

To extract what we called a "structure" dimension, we specified the following scale, which we felt could be argued as representing the rank-ordering of the four stimuli insofaras degree of apparent "structure" is concerned (see GALA choropleths in S,R,& E., 1979)--thus this fixed scale is certainly an arbitrary and subjective quantification of a conceivable perceptual dimension, but one which admittedly has not been specified in terms of any concrete stimulus parameters.

(CFLD----PAVE------EGPV----------VEGN)

The result indicated that only two subjects may have utilized this scale to any "significant" degree in producing their judged differences among the stimuli (Subjects #7 and #34). The average (40 subjects) full weight is only 0.01. We can therefore conclude that this specified "structure" scale did not markedly influence the judged differences among these stimuli given by most subjects.

e. Computer extraction of additional dominant scales.

After the extraction of the three fixed scales, we allowed our scaling model to determine five additional dominant scales with the following results:

Scale 4: (CFLD----------VEGN----EGPV----------PAVE)

Scale 5: (EGPV----------CFLD----PAVE----------VEGN)

Scale 6: (VEGN----PAVE----------CFLD----------EGPV)

Scale 7: (EGPV------PAVE----------VEGN--------CFLD)

Scale 8: (EGPV------PAVE--------------VEGN----CFLD)

By examining the order of the four stimuli in the above scales, it seemed possible to tentatively label and/or at least make the following observations with respect to these five additional scales:

Scale 4: a variation of the second (fixed) texture scale.

Scales 5 and 6 (reverse in order): a variation of the third (fixed) "structure" scale.

Scales 7 and 8 (identical in order): both display a reverse order with respect to the second (fixed) texture scale.

These patterns may be considered reflections of subject-specific perceptual scales; however, they still appear to belong to the

general framework of "texture" and "structure" dimensions. Table 3 (page 15) summarizes the total configuration of perceptual scales in this analysis; the sum of their average "full weights" equals .80, indicating that these 8 scales account for 80% of the total utilization weight.

If we group the weights in Table 3 (page 15) according to the three tentatively labelled, general "dimensions," the pattern shown in Table 4 (page 15) emerges. To even conceptually justify such a summarizing of the values from Table 3 into Table 4, it becomes necessary to distinguish between the concepts of dimensions and scales. Here, a dimension refers to a specific pattern of the ordering of perceptual stimuli regardless of their (distance) ratio; whereas scales refer to statistically different ratios among the stimuli in a given dimension. Thus, subject-specific scales could be viewed as subsets of an appropriately defined (i.e., stimulus-order-specific) dimension.

IV. THE FREE-RUNNING MODEL

Instead of the user fixing specific scales, our new scaling method also allows for the extraction of scales which are based totally on mathematical optimization criteria, analogous to the extraction of factors in factor analysis. Nine scales were extracted by the Master's supersaturation technique in this "free-running" mode using the same, first year (40 subjects), data set (S,R,& E., 1979) these results are summarized in Table 5 (page 16).

TABLE 3: Perceptual Scale Configuration

	"Fixed"				"Remainder"			
Scale No.	1	2	3	4	5	6	7	8
Tentative Labelling	Brightness	$Texture_1$	$Structure_1$	$Texture_2$	$Structure_2$	$Structure_3$	$Texture_3$	$Texture_4$
Average Full Weight	0.45	0.12	0.01	0.10	0.05	0.04	0.02	0.01
Totals	0.80 (sum of 1 through 8)							

TABLE 4: Perceptual Dimensions

Dimension ID	1	2	3	4
Interpretation	Brightness	Texture	Structure	Other
Weight	0.45	0.25	0.10	0.20

TABLE 5: Perceptual Scales From the Free-running Model

	Stimulus Order	Interpreted Dimension	Average Full Weight
Scale 1	P-E-C-V	Brightness	0.59
Scale 2	C-E-P-V	Structure	0.11
Scale 3	C-P-V-E	Other	0.09
Scale 4	P-V-E-C	Other	0.04
<Scale 5	P-E-C-V	Brightness	Computer Only>
Scale 6	V-C-P-E	Texture	0.04
Scale 7	C-V-E-P	Texture	0.02
Scale 8	E-V-C-P	Other	0.02
Scale 9	E-C-V-P	Other	0.03
		Total	.94

With four stimuli, there are 24 possible stimulus orders. From Table 6 (page 18), three reasonably interpretable dimensions (brightness, texture and structure) account for 76 percent of the total full weight, which is analogous to variance. Furthermore, 94 percent of utilization weight can be "explained" by the eight, subject-related (note Scale 5) scales shown in Table 5 (page 16).

It is worth noting that 27 of the 40 subjects had utilization weights summing to 1.00 by the time these nine scales had been extracted, and only two subjects' total utilization weights were still as low as 0.50. Furthermore, 16 of the 27 subjects with complete utilization weights used only two scales, one subject used only one scale and the remaining 10 subjects used the maximum of three possible scales available for any individual subject.

In terms of the frequency of usage of these dimensions, we found that 39 subjects used a scale associated with the "brightness" dimension, four subjects utilized "texture" dimensions and 16 subjects employed "structure" criteria. Finally, 20 or more subjects used "other" (unidentified) scales in the analysis.

We believe that these results cannot detract from, and indeed to a limited extent help to provide additional support for our original hypothesis that there are about three "basic" or "dominant" dimensions, upon which human pattern recognition is built, and that these dimensions appear to be relatable to parameters concerning brightness of the pixels, textural patterning (spatial distribution) among pixels, and the general structure of elements (or primitives) in the image data which can be provided for computer analysis (S.R. & E., 1979).

V. FURTHER DEVELOPMENTS

The new scaling methodology we have thusfar developed is clearly in its early stages, but has demonstrated real advantages and considerable potential for

TABLE 6: Summary of Table 5

	Interpretation	Weight	
Dimension 1:	Brightness	0.59	
Dimension 2:	Texture	0.06	0.76
Dimension 3:	Structure	0.11	
Dimension 4:	Other	0.18	
	Total	0.94	

the problems we are addressing relative to other available techniques. Future developments require careful considerations of the general questions concerning intra- versus inter- individual differences (see above), as well as the following:

a) Further assessment of formal mathematical/statistical considerations of the model, as well as the substantive impact of manipulating its parameters (e.g., cut-offs regarding subspace overlap).

b) Methods for analytically grouping scales into specifiable,stimulus-order-specific dimensions.

c) Issues regarding order of scale entry into the model and the integration of fixed and free-running modes.

d) Other approaches to the specification of scales based on physical (digitized image) data and perceptual outcomes as well as increasing the number of possible scales which any one observer can potentially employ--thus directly showing that subject-specific scales are indeed classifiable as subsets of only about three dimensions.

D. TEXTURE PERCEPTION EXPERIMENTS WITH TWO SETS OF LOW RESOLUTION (GAHA) IMAGE DATA

Our other major effort during this final year of support was concerned with exploring the generality/limitations of results already reported (SR&E, 1979 Annual Report and Section C above). Those results were primarily based on human similarity/difference judgments of high resolution (GALA: low altitude aerial photographs) digitized image data from four relatively distinctive terrain patterns--vegetation (V), cultivated field (C), pavement (P) and edgepavement (E)--as choropleth representations in (15 x 15) greytone patterns. Forty human observers (20 male and 20 female Geography and Psychology students at SUNY-Binghamton who volunteered to provide such judgments and were each paid $2.00 for their efforts) provided the bulk of the data which generally indicated that perceptual similarity/difference judgments typically (though not necessarily always) utilize "brightness", "texture", and

perhaps "structural" dimensions; but the character and weighting of these dimensions clearly display individual (inter- and/or intra-) differences (S.R.& E., 1979 Annual Report; and Section C, above).

I. GENERAL METHODS AND SUBJECTS

To examine the generalizability of the earlier results we generated choropleth representations based on two sets of low resolution (GAHA: high altitude aerial photos) image data. GAHA data set A (Figure 1) consisted of four relatively distinctive terrain patterns--vegetation (V), cultivated field (C1), pavement (P), and mixed pavement (X)--comparable to the GALA (high resolution) data set used initially. GAHA data set B (Figure 2), on the other hand, represented four less distinctive, sub-classes of a particular terrain--vegetation (V), cultivated field (C1), cultivated field (C2), and cultivated field (C3). Again similar to the high resolution (GALA) data set, both of these low resolution (GAHA) image data sets were represented by (15 x 15) greytone patterns.

We will ultimately report the results of the Master's multi-dimensional scaling technique applied to the analysis of similarity/difference judgments from 52 observers (26 male and 26 female Geography and Psychology students at SUNY-Binghamton who volunteered to serve as subjects and were paid $2.00 each for their efforts). All observers judged the similarity of the four patterns within each of the two data sets (A and B, Figures 1 and 2). Half of the subjects of each sex judged Set A first, and then Set B; the other half made judgments concerning Set B first, and then Set A. We also specified a machine solution (*) for each set based on the actual digital measurements of mean brightness and first neighbor contrast in each image pattern (S.R.& E.1979 and Section C above for similar approaches to the analysis of the GALA data set). These digital measures also provide the basis for fixing specific dimensions in the Masters' multi-dimensional technique (Section C, above). Since all 52 subjects judged both Sets A and B, we

FIGURE 1. Data Set A

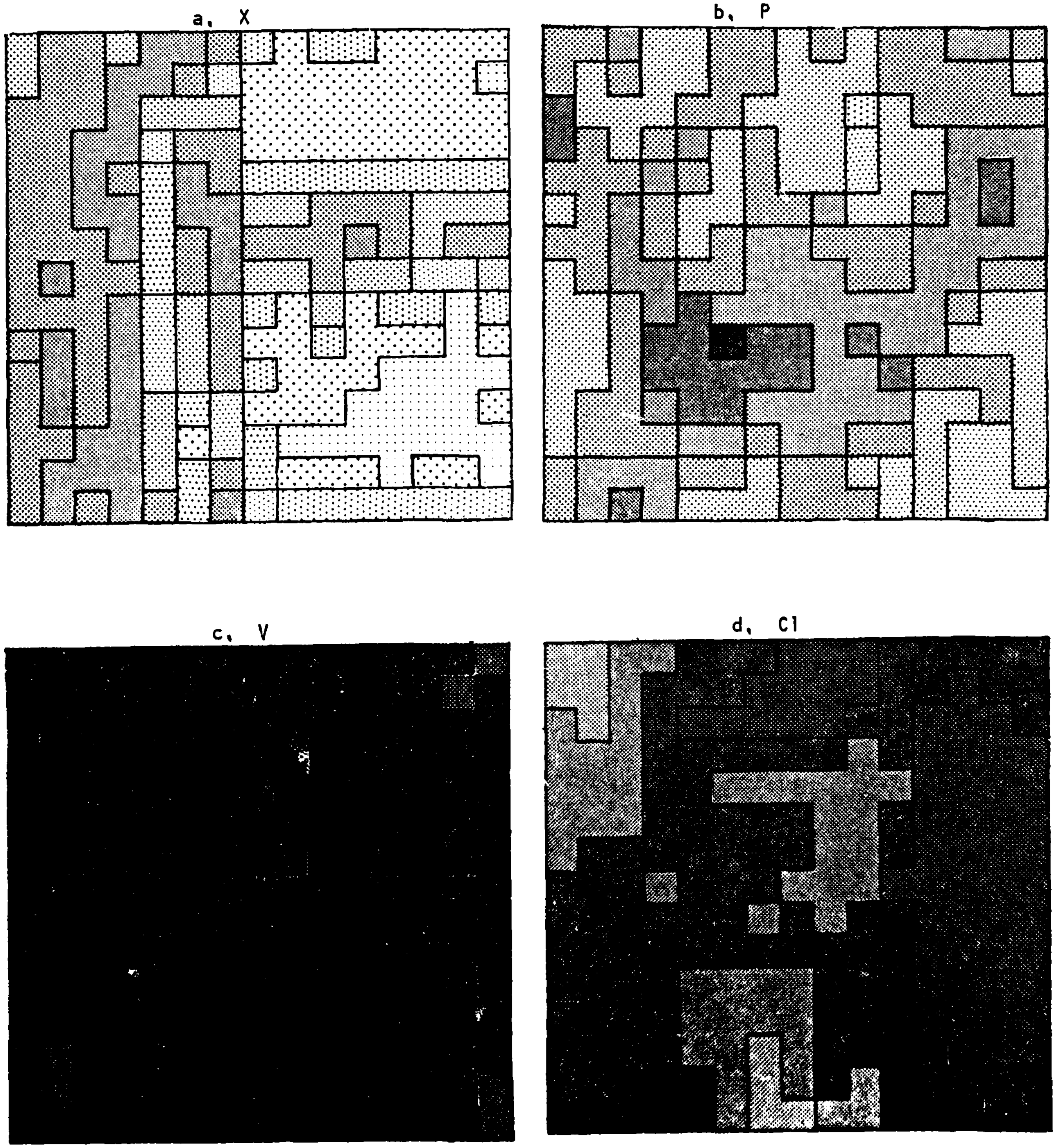
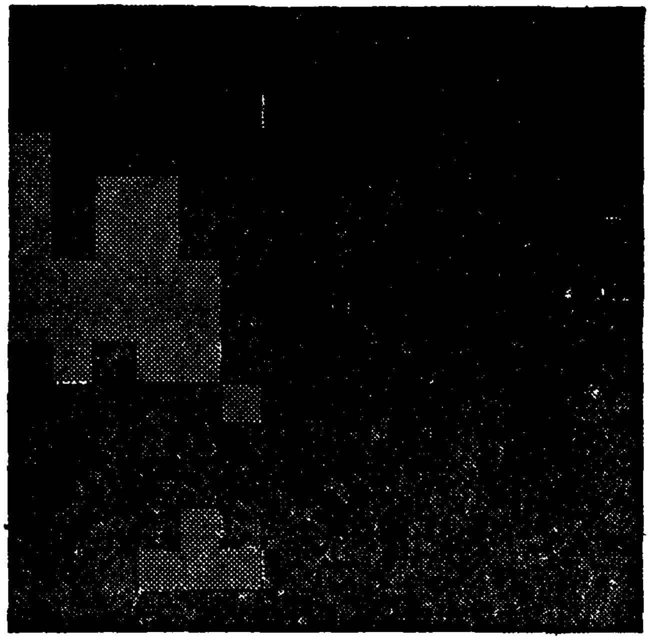
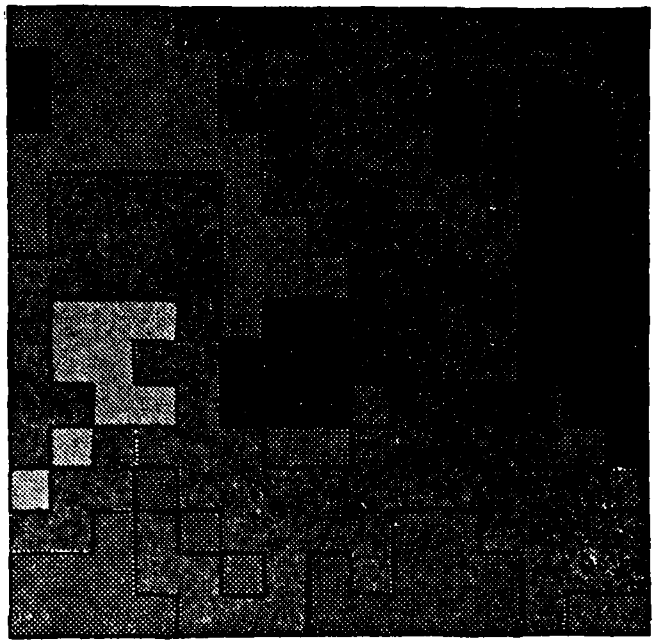


FIGURE 2. Data Set B

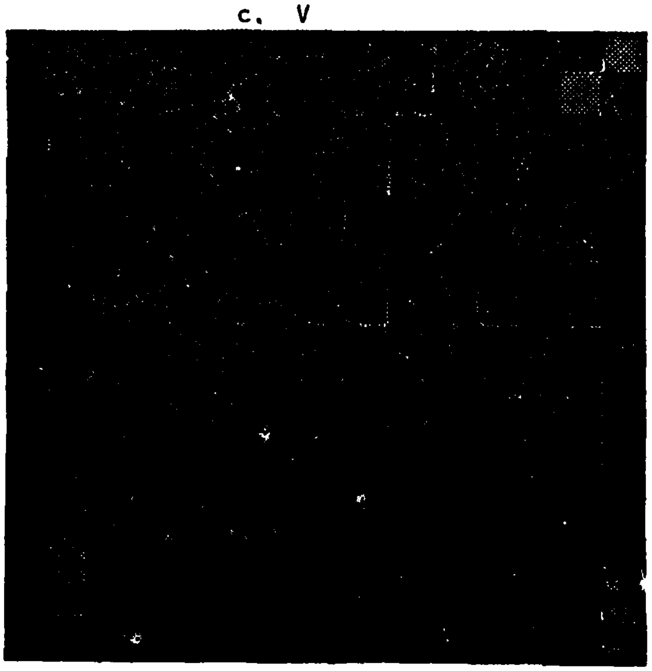
a. C3



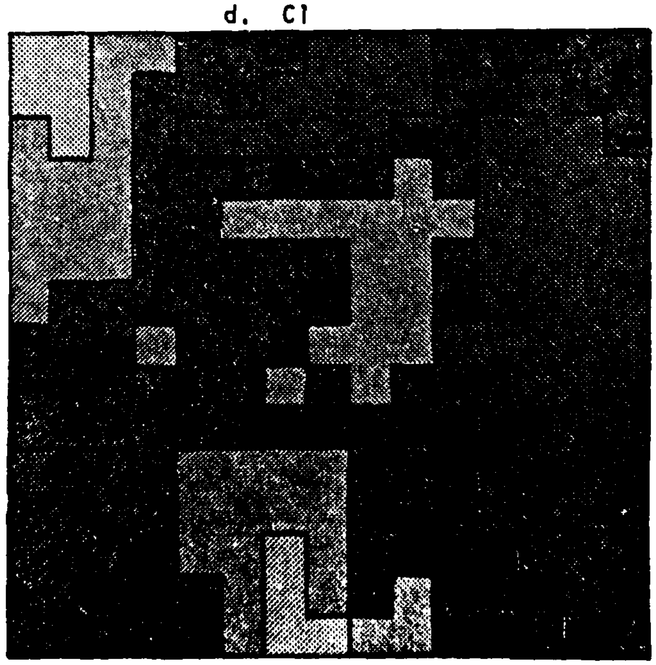
b. C2



c. V



d. C1



will be able to make some specific statements concerning intra-individual differences in the use of scales/dimensions; furthermore, a subset (16) of these 52 subjects also provided judgments of the GALA set (about a year earlier), and comparisons of their results across all three sets (GALA plus GAHA sets A and B) will also be instructive in this regard. First, however, we will present the outcomes of the Masters' supersaturated scaling technique as applied to similarity/difference judgments of GAHA Sets A and B provided by the first 40 subjects examined. This will be done in the context of a free-running model so that direct comparisons of these outcomes with those for 40 subjects judging the GALA set can be made (Section C, above).

II. THE FREE-RUNNING MODEL (MASTERS') ON LOW RESOLUTION (GAHA) SET A (FIRST 40 SUBJECT)--DIRECT COMPARISONS WITH HIGH RESOLUTION (GALA) OUTCOMES

We allowed our new, supersaturated scaling method to extract perceptual scales solely on the basis of optimization criteria. The outcome is summarized in Table 7 (page 24) for GAHA Set A; these summarized results may be compared with the outcome for 40 observers of the GALA (Year 1) perceptual scales (Table 5, page 16 and related text) as determined by the Masters', supersaturated technique in its "free-running" model.

These four stimuli (Figure 1) are based on low resolution (GAHA) terrain types which are otherwise identical to those represented in the high resolution (GALA) data set used in Year 1 and analyzed with the Masters' scaling technique in Section C of this report. The analysis of the perceptual judgments re differences among these patterns showed that 36 of the 40 observers (plus the computer solution) had utilization weights summing to 1.00 by the time these 9 scales were extracted, and only one subject's total weight was less than 0.50;

TABLE 7: Perception Scales From Free-running Model Based on 40 Observers and Computer Solution (*) for the Low Resolution/Distinctive Terrain Patterns (GAHA Set A)

	Stimulus Order+		Average Full Weight*
Scale 1	V-I-P-X		0.65 (0.91)
Scale 2	I-P-V-X		0.15
Scale 3	P-V-I-X		0.08 (0.09)
Scale 4	P-I-X-V		<0.01
Scale 5	P-V-X-I		<0.01
Scale 6	P-E-I-V		0.02
Scale 7	P-I-V-E		<0.01
Scale 8	I-X-V-P		<0.02
Scale 9	X-V-I-P		0.02
		Total	0.97

+See Figure 1 (GAHA, Set A)

I = Cultivated Field 1
V = Vegetation
P = Pavement
X = Mixed Pavement

in the generally comparable GALA set, 27 of 40 subjects (plus computer) had total weights equal to 1.00. Furthermore, the GAHA Set A data indicated that 25 of the 36 observers (plus computer) with complete total weights (1.00) used only two of these 9 scales, 10 of these subjects used their individual maximum of 3, and one employed only 1 scale; in the GALA set (page 17), 16 of 27 subjects used two scales to achieve complete total utilization weights, 10 subjects needed 3 scales, and one required only 1 of the extracted scales. Thus, in these respects (and others, see below), these two data sets appear to be appropriately comparable.

Similarly, the first scale extracted in both data sets (each based on 40 subjects plus the RADC/Hsu computer solution) clearly represents a "brightness" scale--see Figure 1 (GAHA, Set A) and the GALA stimuli (in S.R. & E.1979). In the low resolution (GAHA) set, 35 of the 40 subjects utilized this scale with an average utilization weight of 0.66, and the computer solution weight for this single scale was 0.91; again, the GALA data set (Section C, above) provided comparable, but of course not absolutely identical results--interestingly, the computer solution in the GALA set only weighted the first (subject dominant) brightness scale at 0.22 and apparently utilized its own, unique brightness scale (still stimulus-order-specific,P-E-C-V) much more (weight = .77 on Scale 5; see Table 5, page 16). In addition, when considering comparisons between the two data sets, it is interesting to speculate that the lower resolution (GAHA) images may lead to some "blurring" of the information defining the hypothesized general dimensions of "brightness/texture/structure" relative to the higher resolution (GALA) images.

Furthermore, the first three scales extracted from the 40 subject GAHA, Set A data account for 88% of the discrimination criteria in this data set using the Masters' scaling technique in its free-running mode. In comparison, in the comparable 40 subject GALA set, the first three scales extracted accounted for 79% of the subjects' discrimination criteria. Again, the argument concerning a distinction between general, stimulus-order-specific dimensions and subject-specific scales which may represent specific "distance" relations within such dimensions seems appropriate; but further research and development is required before such distinctions can be fully and adequately "tied to" experimental (stimulus and observer) variables (see Section C, III, above, and general discussion to follow).

III. INTRA-SUBJECT COMPARISONS BASED ON A SUBSET OF INDIVIDUAL JUDGMENTS OF GALA AND GAHA SET A STIMULI

As noted earlier, 16 subjects who provided similarity/difference judgments for the GALA stimuli during 1978-79, also provided judgments for the GAHA stimuli (about one year later). A comparison of their utilization weights on the first 3 scales (and "others") as defined by the 40 subject GALA set and the 40 subject GAHA Set A data using the free-running, Masters' multi-dimensional scaling technique is provided in Table 8 (page 27).

The comparisons delineated in Table 8 serve to emphasize several points which have been discussed earlier: a) observed differences among observers in terms of their weighting of scales extracted from a given data set; b) observed differences among utilization weights within subjects with regard to the nature of such scales in general, and with respect to scales which apparently represent similar,

TABLE 8: Intra-Subject Comparisons (N = 16) of Utilization Weights on Scales Extracted From High Resolution (GALA) and Low Resolution (GAHA, Set A) Data Sets (N = 40) of Four Distinctive Terrain Types

	GALA				GAHA, SET A			
	Stimulus Order Scale				Stimulus Order Scale			
Subject*	(1) P-E-C-V	(2) C-E-P-V	(3) C-P-V-E	(All Others)	(1) V-I-P-X	(2) I-P-V-X	(3) P-V-I-X	(All Others)
a	1.00	0	0	(0)	.85	0	.15	(0)
b	.72	0	0	(.28)	.75	.21	0	(.04)
c	.46	0	0	(.54)	.86	.07	.07	(0)
d	.64	0	.25	(.11)	0	.32	.68	(0)
e	.38	.30	.32	(0)	0	0	0	(1.0)
f	.43	0	0	(.57)	.77	.23	0	(0)
g	.60	0	.40	(0)	.08	.56	0	(0)
h	.81	.06	0	(0)	.92	.08	0	(0)
i	.72	0	.28	(0)	.89	.11	0	(0)
j	.94	0	0	(0)	1.00	0	0	(0)
k	.61	.39	0	(0)	.89	.11	0	(0)
l	0	0	.39	(.61)	.78	.22	0	(0)
m	.73	.16	.11	(0)	0	0	0	(1.0)
n	.57	0	.43	(0)	.81	.09	.10	(0)
o	.95	0	0	(0)	.83	0	0	(.17)
p	.76	0	0	(0)	.93	0	0	(.07)

*arbitrary identification

general (hypothesized) dimensions across data sets; and c) our data and procedures may be (appropriately/necessarily) sensitive to the "blurring" or "merging" of dimensional characteristics (e.g., tone and texture) which must occur as image resolution becomes poorer.

For instance, the first scales extracted from both the 40 subject GALA data set and the 40 subject GAHA (Set A) data set are clearly "brightness" scales in terms of stimulus-order specification. There are, however, marked differences in utilization weights among these same 16 subjects within either of the two sets, and striking differences in how each of these subject weighted such information for one set versus the other. Furthermore, the stimulus order for Scale 1 in GALA was: pavement (P), edgepavement (E), cultivated field (C), and vegetation (V), whereas in GAHA (Set A) it was: vegetation (V), cultivated field 1 (C1), pavement (P), and mixed pavement (X). In both cases, the ordering is certainly appropriate to ordered differences in the average brightness of the four stimuli in each set, but the fact that P was brightest in the high resolution (GALA) set and X in the low resolution (GAHA) set is strongly suggestive of the point that dimensional characteristics may well be "merged" as resolution decreases. Furthermore, even in this limited example, the striking inter- and intra-individual differences among utilization weights speak to the importance of recognizing that while the hypothesis of approximately three, basic dimensions in visual perception may be correct, the idea that intra-dimensional scales can be differentially generated by observers as a function of situation-specific conditions (stimulus parameters, perceived task, perceptual "set", etc.) appears to be highly appropriate. Indeed, this may be how it is that basically the same mechanism (the human nervous system) is capable of displaying such

remarkably beautiful diversity even when operating within the confines of only a few "basic" dimensions. These issues will be addressed further in subsequent sections of this report.

IV. OUTCOMES FROM THE LOW RESOLUTION, COMMON TERRAIN-TYPE (GAHA, SET B) STIMULI BASED ON 40 OBSERVERS

To complete the picture thusfar developed in the context of a common data base of 40 observers (the same individuals who provided the GAHA, Set A analysis presented above), the outcome of the Masters' free-running scaling procedure for these subjects' responses (plus the RADC/Hsu computer solution) to the GAHA, Set B stimuli (Figure 2) are summarized in Table 9 (page 30). After a brief comparison of this outcome with Table 7 (page 24, GAHA, Set A, 40 Subjects), we will expand the data base by 30% (i.e., using all 52 subjects used in obtaining judgments of both GAHA sets) to indicate the kind of stability which our new scaling technique may have concerning the nature of extracted scales (Section V, below).

Again, the first scale derived from the Masters' scaling technique from the judgments of 40 observers (plus the computer solution) is clearly a "brightness" scale with respect to the stimulus order (V-3-2-1) in this low resolution, similar terrain-type data set (GAHA, Set B). This scale, alone accounts for 61% of the discrimination criteria displayed by the subjects (and 89% of that in the computer solution). Thirty-seven of the 40 subjects used this scale. The total of nine extracted scales accounted for 97% of the subject "variance", and 24 of 36 subjects whose total utilization weights equalled 1.0 used two scales, whereas the remaining 12 needed their individual

TABLE 9: Perception Scales From Free-running Model Based on 40 Observers+ and Computer Solution(*) for the Low Resolution/Similar Terrain Type (GAHA, Set B)

Scale	Stimulus Order++		Average Full Weight*
1	V 3 2 1		0.61 (0.89)
2	2 V 3 1		0.11 (0.11)
3	2 3 V 1		0.12
4	V 2 1 3		0.04
5	3 1 2 V		0.04
6	2 V 1 3		<0.04
7	3 2 V 1		<0.01
8	3 2 V 1		<0.01
9	V 2 1 3		<0.01
		Total	0.97

*The averages are for 40 human observers, with the scale weighting for the computer solution alone indicated in parentheses if that weight is >0.

+These are the same 40 subjects on which Table 7 (GAHA, Set A) is based.

++See Figure 2 (GAHA, Set B)

V = Vegetation
1 = Cultivated Field 1
2 = Cultivated Field 2
3 = Cultivated Field 3

maximum of 3 scales to attain total utilization weights of 1.00. The other four observers used only one (n = 3) or two (n = 1) of these scales and received utilization weights ranging from .56-.95. In many respects then, the analysis of this data set is comparable to those previously reported for different stimulus configurations, and also illustrates the importance of distinguishing between dimensions and scales which was initially discussed in Section C, above. Rather than pursue these issues further at this point, we will now turn to the analyses of both GAHA sets (A and B) based upon the largest data base (n = 52) which we have generated to date.

V. ANALYSES OF THE LOW RESOLUTION DATA SETS BASED ON 52 OBSERVERS AND THE COMPUTER SOLUTIONS

Expanding the GAHA, 40 subject, data base (above) by 30% (using additional subjects drawn from the same population available to us) allowed us to consider the stability of our new Masters' scaling technique in both Set A (different terrain types) and Set B (similar terrain types). As noted earlier, this 52 subject data base (Geography and Psychology students at SUNY-Binghamton) consisted of 26 males and 26 females, each of whom judged Set A and Set B stimulus sets; half of each gender judged Set A (different terrain types) first and the other half judged Set B (similar terrain types) first.

a. <u>GAHA, Set A: Low Resolution/Distinctive Terrain Types</u>

Table 10 (page 32) summarizes this expanded-data-base analysis for GAHA, Set A so that it may be compared with the "free-running" analysis of the same stimulus set using only 40 subjects (Table 7, page 24). As in the 40 subjects analysis, 9 scales were extracted; 98% of the subject "variance" was accounted for by these scales compared with 97% in the smaller (40 subject)

TABLE 10: Perception Scales From Free-running Model Based on 52 Observers and Computer Solution (*) for the Low Resolution/ Different Terrain Types (GAHA, Set A)

Scale	Stimulus Order		Average Full Weight*
1	V-I-P-X		.67 (.91)
2	I-P-V-X		.15
3	P-V-X-I		.08 (.09)
4	P-I-X-V		.01+
5	P-X-I-V		.02
6	V-P-X-I		.01+
7	P-I-V-X		.01+
8	V-P-I-X		.01
9	I-P-V-X		.01
		Total	.98

*The averages are for 52 human observers, with the scale weights for the computer solution alone indicated in parentheses if that weight is >0.

analysis. In both analyses the first scale extracted displayed the same stimulus order which clearly represents a "brightness" scale of the four stimuli in the set; furthermore, that scale accounted for 67% of the total possible subject utilization weights in the larger (N=52) analysis (Table 10, page 32) and 65% in the smaller (N=40) analysis (Table 7, page 24). The second scale extracted in both analyses also displayed a common stimulus order (I-P-V-X) and accounted for 15% of the total possible subject utilization weights in both cases. The additional 7 scales extracted in each analysis (accounting, in total, for some 18-20% of subject "variance") were not identical in stimulus order; but it is interesting to note that the RADC/Hsu computer solution had a full weight of .09 on the third scale extracted in both analyses, despite the fact that Scale 3 had a different stimulus order in the two analyses. Indeed, stimuli I and X were placed very near one another on both scales even though their order was reversed from one analysis to the other. In general, the stability of the scaling procedure appears to be quite satisfactory as assessed by this comparison.

b. GAHA, Set B: Low Resolution/Similar Terrain Types

Table 11 (page 34) summarizes the "free-running", Masters' scaling analysis of the low resolution, similar terrain type (Set B) judgments of 52 subjects (plus computer solution). This can be directly compared with the same analysis based on the smaller (N = 40) sample and already summarized in Table 9 (page 30). As in the 40 subject sample, 9 scales were extracted; these scales accounted for 96% of the total possible subject "variance" compared with 97% in the 40 observer analysis. Again, the first scale extracted in both analyses clearly represents a "brightness" scale (V-3-2-1); that first scale accounted for 60% of the total possible subject utilization weights in the larger (N = 52)

TABLE 11: Perceptual Scales From Free-running Model Based on 52 Observers and Computer Solution (*) for the Low Resolution/ Similar Terrain Types (GAHA, Set B)

Scale	Stimulus Order		Average Full Weight*
1	V-3-2-1		.60 (.89)
2	1-3-V-2		.12 (.11)
3	3-2-1-V		.08
4	2-V-3-1		.03+
5	2-3-V-1		.05+
6	3-1-V-2		.04+
7	V-1-2-3		.01
8	2-3-1-V		.01+
9	3-2-1-V		<.01
		Total	.96

*The averages are for 52 human observers, with the scale weights for the computer solution alone indicated in parentheses if that weight is >0.

analysis (Table 11) and 61% in the smaller (N = 40) analysis (Table 9). The second scale extracted in each analysis was a reflection (reverse order) of the other (2-V-3-1 in the smaller, Table 9 analysis; 1-3-V-2 in the larger, Table 11 analysis); in both analyses, the second scale accounted for 11-12% of total subject "variance", and the utilization weight for the RADC/Hsu computer solution also was 0.11 in both cases. The remaining 7 scales obtained in each analysis (accounting, in total, for some 24-25% of subject "variance") were not the same with respect to stimulus order. This again raises the question of scales versus dimension which was introduced in Section C and has been noted explicitly and implicitly at various points above; in this regard, it is important to recall that the Masters' scaling technique extracts scales which are not orthogonal--the matter of relationships among these scales will be specifically addressed in Section D. VI, below. In any event, the comparisons of smaller (N = 40) and larger (N = 52) data-based analyses of the GAHA stimuli here (Set B) and in a) above (Set A) suggest that the Masters', supersaturated, multi-dimensional scaling technique is reasonably stable.

c. <u>Inter- and Intra-Individual Differences Among Utilization Weights Based on Analyses of GALA (N = 40 plus computer) and GAHA (N = 52 plus computer) Data</u>

The important issues concerning inter- and intra-individual differences are legion in psychological data in general and have already been introduced and addressed in previous sections of this final report insofaras our data are concerned. Given the: 1) results thus far reported; 2) factorially arranged GAHA data with respect to gender and order of judging Set A and B;

3) subset (N = 16) of observers who provided both GAHA data, and GALA judgments (in year I); and 4) conceptual issues concerning scales versus dimensions (see above, and D. VI below), a presentation of individual utilization weights for the first ("brightness"), clearly consistent, scales extracted from free-running Masters' scaling applied to the largest available GAHA (N = 52) and GALA (N = 40) sets would appear to be the most useful and effective way of summarizing and demonstrating aspects of our findings with respect to the individual differences question(s). Table 12 (page 37) provides just such data, arranged to provide a description of these outcomes with respect to the gender-by-order conditions imposed during the collection of GAHA, Set A and Set B judgments.

The individual utilization weights (Table 12, page 37) on each of the first "brightness" scales extracted (accounting for 60% or more of the total subject discrimination criteria in each set) by Masters' scaling (free-running) analysis of the stimulus sets (GAHA, A and B and GALA) dramatize the individual (inter- and intra-) differences issue. For instance, weights literally range from 0-1.00, but this should not be construed to indicate that some subjects, sometimes *ignore* "brightness" as a *dimension*--indeed, subject debriefings (see Section E, below) always resulted in some mention of intensitive/brightness considerations. Zero values "simply" mean that the subject's similarity/difference judgments did not weight that particular scale (distance relationships, etc.) well enough to be given a utilization weight according to the optimization criteria employed in the scaling analysis (see Section C and related considerations throughout). Until such matters are more completely addressable via fully quantifiable, psychophysical mapping of stimulus parameters and psychological dimensions for complex data (see also Sections D. VI and E below), questions of

TABLE 12: Individual Utilization Weights on the First Scales ("Brightness" Scales) Extracted by Masters' Scaling on the N = 52 GAHA Sets (A and B) and the N = 40 GALA*Set for a Subset of 16 Subjects Common to Both GALA and GAHA Data Bases : Note the Categorization With Regard to Gender and Order of Judging the GAHA Sets

	Set A Judged First				Set B Judged First			
	Subjects	A	B	[GALA]*	Subjects	A	B	[GALA]*
	3	.86	.74		2	.80	.17	
	5	.71	.62		4	0	0	
	7	.47	.42		8	.92	.70	
	9	.90	.86		16	.86	.82	[.46]
	11	.94	.89		20	.08	.60	[.60]
	13	.24	.63		24	.89	.90	[.72]
Male	15	.89	.81		26	.35	.44	
	17	.87	.69	[.64]	32	.81	.75	[.57]
	19	.77	.96	[.43]	40	.96	.90	
	31	0	0	[.73]	42	.80	.85	
	33	.83	.80	[.95]	44	0	0	
	45	.54	.20		48	.87	.84	
	51	.78	.81		52	0	0	
	$\bar{X}$	.68	.65	[.69]	$\bar{X}$	.56	.54	[.59]
	1	.89	.83		6	.67	.72	
	21	.77	.76		10	.85	.69	[1.00]
	23	.90	.73		12	.79	.65	
	25	1.00	.70	[.94]	14	.75	.18	[.72]
	27	.89	.74	[.61]	18	0	0	[.38]
	29	.78	.96	[0]	22	.92	.68	[.81]
Female	35	.93	.85	[.76]	28	.07	.12	
	37	0	.17		30	.76	.68	
	39	.76	.53		34	.83	.74	
	41	.81	.52		36	.85	.65	
	43	.80	.43		38	.72	.64	
	47	.64	.62		46	.81	.59	
	49	.67	.67		50	.90	.81	
	$\bar{X}$	.76	.65	[.58]	$\bar{X}$	.69	.55	[.73]

Weight for Computer Solutions on "Brightness" Scales

A	B	GALA
(.91)	(.89)	(.22) and (.77)

*Judgments during Year I, see Section D. IV.
See Table 5, page 16.

how stimulus parameters, subject differences (e.g., sex, training, etc.) and/or judgment/task conditions (e.g., order, instructions, etc.) may influence a given individual's perceptual weighting of a basic dimension such as "brightness," are necessarily premature. Thus, while the order-by-gender conditions delineated in Table 12 are potentially intriguing, the issue of how extracted scales relate to hypothesized, basic, psychological dimensions must be unravelled.

VI. OBSERVED RELATIONS AMONG EXTRACTED PERCEPTUAL SCALES

The Masters', supersaturated, multidimensional scaling technique which we have developed has enabled us to extract scales utilized by individual observers in judging "overall visual differences" among stimuli based on representations of achromatic aerial photographs and defined via digitized information in the context of the RADC/Hsu (3 x 3 moving/overlapping grid) system. For both descriptive and theoretical reasons, the extracted scales were allowed to be oblique, rather than being forced to orthogonal solutions. Throughout the presentation of our findings we have stressed the importance of distinguishing between these scales and the potential/probable existence of more basic dimensions, highlighting examples in our data which have indicated clearly that the scale versus dimension problem is indeed a cogent and highly complex one.

Table 13 (page 39) summarizes aspects of the relations (as assessed by simple, pairwise correlations) between scales extracted by the Masters', free-running solutions of the GAHA and GALA data sets. Perusal of Table 13 clearly indicates that the highest correlations observed between these various extracted scales typically are quite high (often $\pm$ .85 or higher). This fact alone further serves to bring home the point that individual differences in utilization weights of such scales (or scaling techniques in general) do <u>not</u> imply that inter- and/or intra-individual differences in such weights result from observers' (including

TABLE 13. Highest (+ or -) Simple Correlations Between Scales Extracted via Masters' (Free-Run) Scaling

A. Low Resolution/Different Terrain Types: GAHA, Set A (N = 52 plus Computer)

Scales		Correlation	Scales		Correlation
1 & 5	=	- .84	6 & 8	=	+ .91
2 & 9	=	+ .86	7 & 2	=	+ .85
3 & 6	=	+ .85	(8 & 6 = 6 & 8	=	+ .91)
4 & 5	=	+ .87	8 & 3	=	+ .76
(5 & 4 = 4 & 5	=	+ .87)	(9 & 2 = 2 & 9	=	+ .86)
(5 & 1 = 1 & 5	=	- .84)	9 & 7	=	+ .70
5 & 2	=	+ .42			

B. High Resolution/Different Terrain Types: GALA (N = 40 plus Computer), Year I

Scales		Correlation	Scales		Correlation
1 & 5	=	+ .93	6 & 1	=	- .79
2 & 7	=	+ .80	(7 & 2 = 2 & 7	=	+ .80)
3 & 8	=	- .96	7 & 4	=	- .77
4 & 5	=	+ .81	(8 & 3 = 3 & 8	=	- .96)
(5 & 1 = 1 & 5	=	+ .93)	8 & 9	=	+ .86
(5 & 4 = 4 & 5	=	+ .83)	(9 & 8 = 8 & 9	=	+ .86)
5 ¢ 6	=	- .74	9 & 4	=	- .74

C. Low Resolution/Different Terrain Types: GAHA, Set B (N = 52 plus Computer)

Scales		Correlation	Scales		Correlation
1 & 9	=	+ .29	6 & 9	=	+ .90
2 & 4	=	- .97	(7 & 3 = 3 & 7	=	- .98)
3 & 7	=	- .98	7 & 8	=	- .89
(4 & 2 = 2 & 4	=	- .97)	8 & 3	=	+ .95
4 & 6	=	- .82	(9 & 6 = 6 & 9	=	+ .90)
5 & 2	=	- .89	9 & 7	=	- .85

machine solutions) employing completely unique basic dimensions. Rather, such relations among extracted scales suggest that unique scales are more likely the result of individuals creating idio-perceived, task-specific-modulational/combinational weightings of a few basic dimensions which are produced from common characteristics shared by neural (or machine) processing of visual features which must be based on "building blocks" of information such as intensity, spatial distribution and general structure of elements.

For instance, from the data summarized in Table 13, the GAHA, Set A analysis (Table 13, part A) produced the number scales which appear to "cluster" as follows: 1, 4, and 5/3, 6, and 8/2, 7, and 9; similarly, for the GALA data (Table 13, part B): 1, 5, and 6/2 and 7/3, 8, and 9; and, for the GAHA, Set B analysis (Table 13, part C): 1/2, 4, and 5/3, 7, and 8. Of course, such clusters of scales are not completely independent of one another, and scales not included in any of the inferred clusters appear to have something in common with each of the clusters in any of the separate analyses. Clearly, such considerations demand further study (see above especially Section C. III and V, and Section E, below, of this final report); but the general approach and procedures we have developed appear to offer considerable promise in this regard. We should point out again, however, that while the idea of stimulus-order-specificity among scales is appealing, such "handy" scale characteristics alone cannot directly and/or completely identify the dimensional characteristics among scales derived in such a manner. Finally, it should be recalled that our new scaling technique possesses the important capability of using "fixed" scales (see Section C of this report), especially for true psychophysical mapping of complex, real-world stimuli as well as further examination of the matters just discussed. But to attempt to employ that capability in any conclusive fashion at this point in our development of approaches to that problem, and pattern recognition issues in general, would be premature.

E. GENERAL DISCUSSION

Virtually anyone concerned with the general problem of pattern recognition in man and/or machine is fully appreciative of its importance and complexity. We certainly cannot claim to have solved these problems in the two years of research so generously and insightfully sponsored by AFOSR, and summarized in this final report. However, we can make some significant points regarding our approaches and findings.

The still very exciting, promising and eclectically supported idea (cf. Sections A and B and reference Section F) that a few (perhaps about three) dimensions are basic and critical to the pattern recognition problem for man or machine clearly remains viable. Indeed, subject debriefings in our research (cf. also Section D. V.c.), and virtually any other concerned with judgments of visual patterns, generally corroborate the idea that they "work with" such notions as "brightness" and "complexity." However, it also is clear that those notions are not clearly defineable and/or equally "weighted" in the verbal reports of human observers, nor do they necessarily refer to the same "macro-texturally" definable characteristics of the stimulus patterns from one subject to the next, or even from one judging session to the next within the same observer (see also Table 8, page 27, and Table 12, page 37). Nonetheless, the basic distal stimulus informational "building-blocks" for such dimensions must be invariantly present in the "micro-textural" characteristics of physically represented patterns, and thus specifiable by techniques such as those employed in the RADC/Hsu system which uses moving and overlapping pixel grids to extract general density as well as spatial relationship data from images at a micro-textural level (see Sections A and B and all "computer solution" results in all analyses presented in this report; 1978-79 Annual Report (S.R.& E); and Hsu and Burright, 1980).

All of the above considerations are reflected clearly in the various scales which we have been able to extract using the newly developed Masters', super-saturated, multi-dimensional scaling technique (Section C) in analyzing judgments (human and computer) of data sets based on complex/real-world patterns involving both high (GALA) and low (GAHA) resolution imagery of different (GALA and GAHA, Set A) or similar (GAHA, Set B) terrain types (Section D). In this context, our research has served to emphasize in a rather unique way the problems of scaling techniques in general, and of those such as Takane, et al (1977), in particular. Thus, our work has provided several new perspectives from which the kinds of further methodological, experimental, and theoretical developments which will be required to produce effective in-roads to understanding this general problem area may be viewed.

The distinction between scales and dimensions which we have emphasized throughout this final report (cf. especially Section D. VI), cannot be ignored in the considerations just reviewed. An objective way(s) to "cluster" such specific (extracted) scales into representations of appropriate dimensions which can be related to and based upon stimulus, task and subject specifiable characteristics must be developed before a fuller understanding of this exquisitely complex and cogent problem of pattern recognition will be achieved. If such a psychophysical-mapping of complex/real-world imagery is developed--and our research suggest not only that it may be done, but also provides some new perspectives on how it could be developed--then we will be able to better explore, quantify and ultimately understand the extra-ordinary modulating influences which subject and situational/task-specific factors can produce in the processing of information arising from the stimulus-informational "building-blocks" present at the "micro-textural"

level of any image data. The data and ideas presented in this final report of our AFOSR sponsored research have produced some new and clear approaches and perspectives from which to attack the enormous problems in this general area; (hopefully) they will contribute significantly to answers concerning the extremely important questions about pattern recognition and the effective handling of information by man and machine.

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